1a

In [1]:

```
N=int(input())
board=[[0]*N for _ in range(N)]
def is_attack(i,j):
    for k in range(N):
        if(board[i][k]==1) or (board[k][j]==1):
            return True

    for k in range(N):
        for l in range(N):
            if(k+l==i+j)or (k-l==i-j):
                if board[k][l]==1:
                    return True
    return False

def q(n):
    if n==0:
        return True

    for i in range(N):
        for j in range(N):
            if(not(is_attack(i,j)) and board[i][j]!=1 ):
                board[i][j]=1
                if q(n-1)==True:
                    return True
                board[i][j]=0
    return False

q(N)
for i in board:
    print(i)
```

```
7
[1, 0, 0, 0, 0, 0, 0]
[0, 0, 1, 0, 0, 0, 0]
[0, 0, 0, 0, 1, 0, 0]
[0, 0, 0, 0, 0, 0, 1]
[0, 1, 0, 0, 0, 0, 0]
[0, 0, 0, 1, 0, 0, 0]
[0, 0, 0, 0, 0, 1, 0]
```

1b

In [ ]:

```
```

1c

In [2]:

```
#bfs
from queue import PriorityQueue
v = 14
graph = [[] for i in range(v)]


def best_first_search(source, target, n):
    visited = [False] * n
    visited[0] = True
    pq = PriorityQueue()
    pq.put((0, source))
    while pq.empty() == False:
        u = pq.get()[1]
        print(u, end=" ")
        if u == target:
            break

        for v, c in graph[u]:
            if visited[v] == False:
                visited[v] = True
                pq.put((c, v))
    print()


def addedge(x, y, cost):
    graph[x].append((y, cost))
    graph[y].append((x, cost))

addedge(0, 1, 3)
addedge(0, 2, 6)
addedge(0, 3, 5)
addedge(1, 4, 9)
addedge(1, 5, 8)
addedge(2, 6, 12)
addedge(2, 7, 14)
addedge(3, 8, 7)
addedge(8, 9, 5)
addedge(8, 10, 6)
addedge(9, 11, 1)
addedge(9, 12, 10)
addedge(9, 13, 2)

source = 0
target = 9
best_first_search(source, target, v)
```

```
0 1 3 2 8 9
```

1d

In [3]:

```
from collections import defaultdict

visited=defaultdict(lambda:False)

j1,j2,aim=4,3,2

def w(amt1,amt2):
    if (amt1==2 and amt2==0) or (amt1==0 and amt2==2):
        print(amt1,amt2)
        return True
    if visited[(amt1,amt2)]==False:
        print(amt1,amt2)

        visited[(amt1,amt2)]=True

        return(w(0,amt2) or
               w(amt1,0) or
               w(j1,amt2)or
               w(amt1,j2) or
               w(amt1+min(amt2,j1-amt1),amt2-min(amt2,j1-amt1))or
               w(amt1-min(amt1,j2-amt2),amt2+min(amt1,j2-amt2))
        )
    else:
        return False

w(0,0)
```

```
0 0
4 0
4 3
0 3
3 0
3 3
4 2
0 2
```

Out[3]:

```
True
```

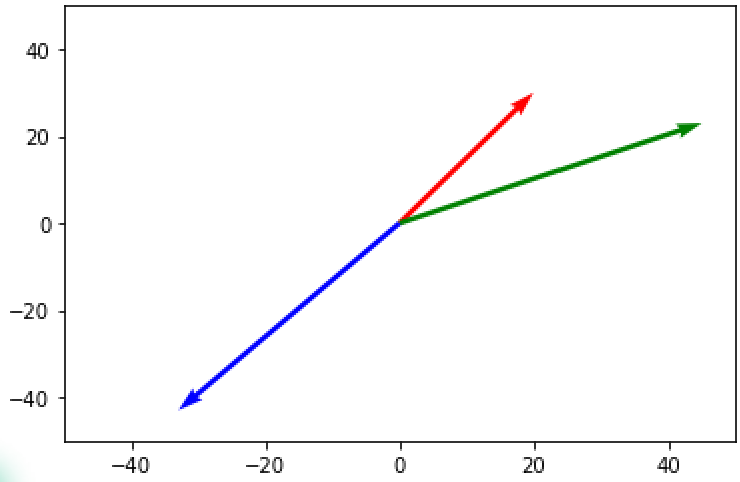
2 2d AND 3D

In [4]:

```
import numpy as np
import matplotlib.pyplot as plt

def plt2d(v,color):
    origin=[0,0]
    plt.quiver(*origin,*v,color=color,angles='xy',scale_units='xy',scale=1)

def plt3d(ax,v,color):
    ax.quiver(*[0,0,0],*v,color=color)
```

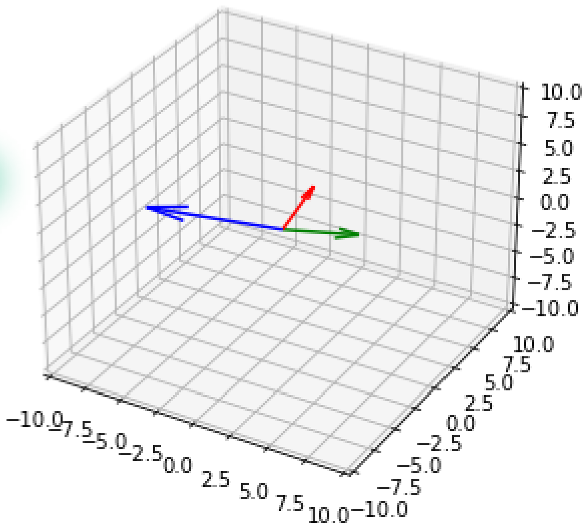
In [5]:

```
#2d
x=[20,30]
y=[45,23]
z=[-33,-43]

plt.xlim(-50,50)
plt.ylim(-50,50)

plt2d(x,'r')
plt2d(y,'g')
plt2d(z,'b')
```



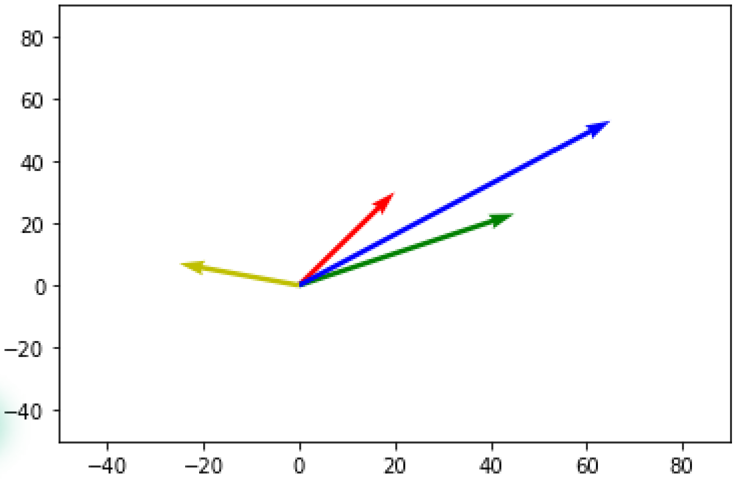
In [6]:

```
#3d

v1=[1, 2, 3]
v2=[-7, -4, 2]
v3=[3, 4, -2]

fig=plt.figure(figsize=(5,5))
ax=plt.axes(projection='3d')


plt.xlim([-10,10])
plt.ylim([-10,10])
ax.set_zlim([-10,10])

plt3d(ax,v1,'r')
plt3d(ax,v2,'b')
plt3d(ax,v3,'g')
```



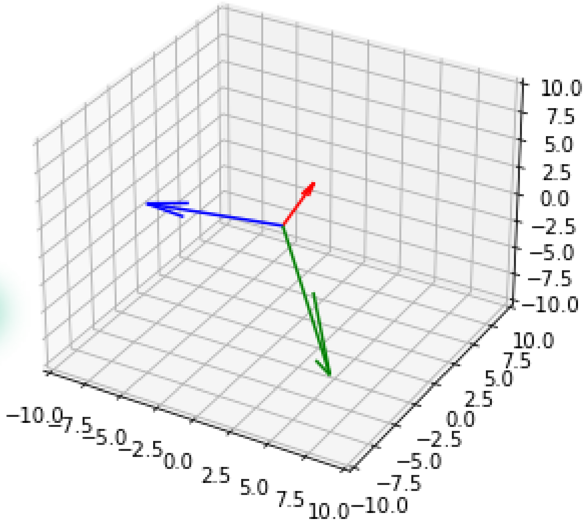
In [7]:

```
#vector addition
x1=np.array([20,30])
y1=np.array([45,23])

plt.xlim([-50,90])
plt.ylim([-50,90])

plt2d(x1,'r')
plt2d(y1,'g')
plt2d(x1+y1,'b')

#subtraction
plt2d(x1-y1,'y')
```



In [8]:

```
#cross product
j1=[1, 2, 3]
j2=[-7, -4, 2]

fig=plt.figure(figsize=(5,5))
ax=plt.axes(projection='3d')


plt.xlim([-10,10])
plt.ylim([-10,10])
ax.set_zlim([-10,10])

plt3d(ax,j1,'r')
plt3d(ax,j2,'b')
plt3d(ax,np.cross(j1,j2),'g')
```



3

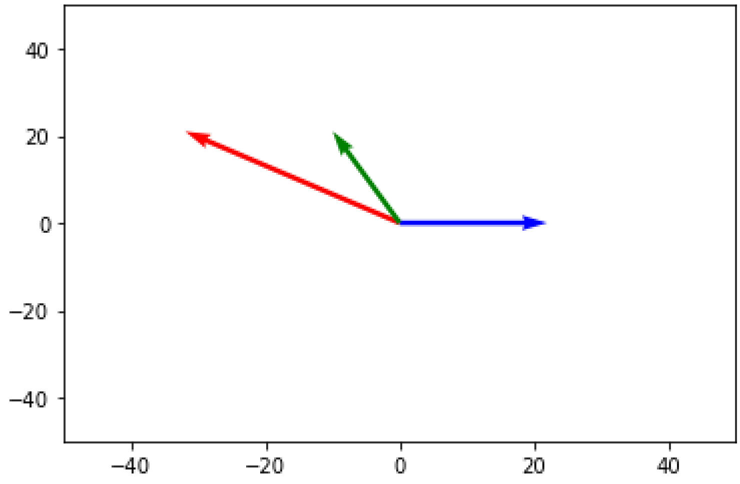
In [9]:

```
a=np.array([-32,21])
b=np.array([22,0])
maga=np.linalg.norm(a)
magb=np.linalg.norm(b)
dot=np.dot(a,b)
s=np.add(a,b)

if (maga*magb>=dot):
    print('sch')
else:
    print('no sch')
if (np.add(maga,magb)>=np.linalg.norm(s)):
    print('tri')
else:
    print('no tri')

plt.xlim([-50,50])
plt.ylim([-50,50])

plt.quiver(*[0,0],*a,angles='xy',scale=1,scale_units='xy',color='r')
plt.quiver(*[0,0],*b,angles='xy',scale=1,scale_units='xy',color='b')
plt.quiver(*[0,0],*(a+b),angles='xy',scale=1,scale_units='xy',color='g')
```

```
sch
tri
```

Out[9]:

```
<matplotlib.quiver.Quiver at 0x21b6499b9a0>
```



4

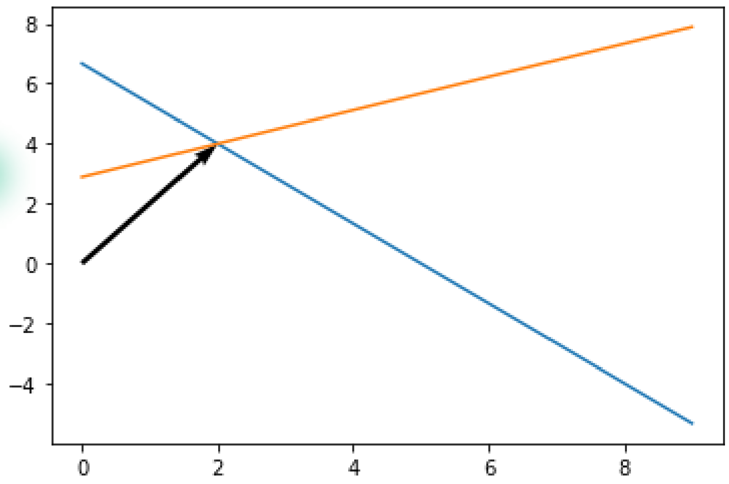
In [10]:

```
import matplotlib.pyplot as plt
import numpy as np
a=np.array([[4,3],[-5,9]])
b=np.array([20,26])
print('inverse=',np.linalg.inv(a))
e=np.linalg.solve(a,b)
print('the sol',e)
xp=np.linspace(0,9,1000)
y1=(20-4*xp)/3
y2=(26+5*xp)/9
plt.plot(xp,y1)
plt.plot(xp,y2)
plt.quiver(*[0,0],*[2,4],scale=1,scale_units="xy",angles='xy',units='xy')
```

```
inverse= [[ 0.17647059 -0.05882353]
 [ 0.09803922  0.07843137]]
the sol [2. 4.]
```

Out[10]:

```
<matplotlib.quiver.Quiver at 0x21b649f4430>
```



In [ ]:

```

```

#5

In [11]:

```
import pandas as pd
import numpy as np
import seaborn as sns
s=sns.load_dataset('iris')
s.to_csv(r"C:\Users\kisha\Desktop\k.csv")

data=pd.read_csv(r"C:\Users\kisha\Desktop\k.csv")
data.head()
```

Out[11]:

	Unnamed: 0	sepal_length	sepal_width	petal_length	petal_width	species
0	0	5.1	3.5	1.4	0.2	setosa
1	1	4.9	3.0	1.4	0.2	setosa
2	2	4.7	3.2	1.3	0.2	setosa
3	3	4.6	3.1	1.5	0.2	setosa
4	4	5.0	3.6	1.4	0.2	setosa

In [12]:

```
data.count()
```

Out[12]:

```
Unnamed: 0      150
sepal_length    150
sepal_width     150
petal_length    150
petal_width     150
species         150
dtype: int64
```

In [13]:

```
data.value_counts('sepal_length')
```

Out[13]:

```
sepal_length
5.0    10
6.3     9
5.1     9
5.7     8
6.7     8
6.4     7
5.8     7
5.5     7
5.4     6
6.1     6
5.6     6
6.0     6
4.9     6
4.8     5
6.5     5
6.2     4
5.2     4
4.6     4
7.7     4
6.9     4
7.2     3
5.9     3
4.4     3
6.8     3
4.7     2
6.6     2
7.4     1
7.6     1
7.3     1
4.3     1
7.1     1
7.0     1
5.3     1
4.5     1
7.9     1
dtype: int64
```

In [14]:

```
data.sort_values(by='sepal_length',inplace=False,axis=0,ascending=False)
```

Out[14]:

	Unnamed: 0	sepal_length	sepal_width	petal_length	petal_width	species
131	131	7.9	3.8	6.4	2.0	virginica
135	135	7.7	3.0	6.1	2.3	virginica
122	122	7.7	2.8	6.7	2.0	virginica
117	117	7.7	3.8	6.7	2.2	virginica
118	118	7.7	2.6	6.9	2.3	virginica
...	...	...	...	...	...	...
41	41	4.5	2.3	1.3	0.3	setosa
42	42	4.4	3.2	1.3	0.2	setosa
38	38	4.4	3.0	1.3	0.2	setosa
8	8	4.4	2.9	1.4	0.2	setosa
13	13	4.3	3.0	1.1	0.1	setosa

150 rows × 6 columns

In [15]:

```
data.iloc[1,2]=float("NaN")
data.head()
data.dropna(inplace=False)
```

Out[15]:

	Unnamed: 0	sepal_length	sepal_width	petal_length	petal_width	species
0	0	5.1	3.5	1.4	0.2	setosa
2	2	4.7	3.2	1.3	0.2	setosa
3	3	4.6	3.1	1.5	0.2	setosa
4	4	5.0	3.6	1.4	0.2	setosa
5	5	5.4	3.9	1.7	0.4	setosa
...	...	...	...	...	...	...
145	145	6.7	3.0	5.2	2.3	virginica
146	146	6.3	2.5	5.0	1.9	virginica
147	147	6.5	3.0	5.2	2.0	virginica
148	148	6.2	3.4	5.4	2.3	virginica
149	149	5.9	3.0	5.1	1.8	virginica

149 rows × 6 columns

In [16]:

```
data.iloc[4,2]
```

Out[16]:

```
3.6
```

In [17]:

```
data.describe()
```

Out[17]:

	Unnamed: 0	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	149.000000	150.000000	150.000000
mean	74.500000	5.843333	3.057718	3.758000	1.199333
std	43.445368	0.828066	0.437311	1.765298	0.762238
min	0.000000	4.300000	2.000000	1.000000	0.100000
25%	37.250000	5.100000	2.800000	1.600000	0.300000
50%	74.500000	5.800000	3.000000	4.350000	1.300000
75%	111.750000	6.400000	3.300000	5.100000	1.800000
max	149.000000	7.900000	4.400000	6.900000	2.500000

In [18]:

```
type(data)
```

Out[18]:

```
pandas.core.frame.DataFrame
```

In [19]:

```
data.loc[(data.sepal_length)>3]
```

Out[19]:

	Unnamed: 0	sepal_length	sepal_width	petal_length	petal_width	species
0	0	5.1	3.5	1.4	0.2	setosa
1	1	4.9	NaN	1.4	0.2	setosa
2	2	4.7	3.2	1.3	0.2	setosa
3	3	4.6	3.1	1.5	0.2	setosa
4	4	5.0	3.6	1.4	0.2	setosa
...	...	...	...	...	...	...
145	145	6.7	3.0	5.2	2.3	virginica
146	146	6.3	2.5	5.0	1.9	virginica
147	147	6.5	3.0	5.2	2.0	virginica
148	148	6.2	3.4	5.4	2.3	virginica
149	149	5.9	3.0	5.1	1.8	virginica

150 rows × 6 columns

In [20]:

```
data.drop(["sepal_length"],axis=1)
```

Out[20]:

	Unnamed: 0	sepal_width	petal_length	petal_width	species
0	0	3.5	1.4	0.2	setosa
1	1	NaN	1.4	0.2	setosa
2	2	3.2	1.3	0.2	setosa
3	3	3.1	1.5	0.2	setosa
4	4	3.6	1.4	0.2	setosa
...	...	...	...	...	...
145	145	3.0	5.2	2.3	virginica
146	146	2.5	5.0	1.9	virginica
147	147	3.0	5.2	2.0	virginica
148	148	3.4	5.4	2.3	virginica
149	149	3.0	5.1	1.8	virginica

150 rows × 5 columns

6

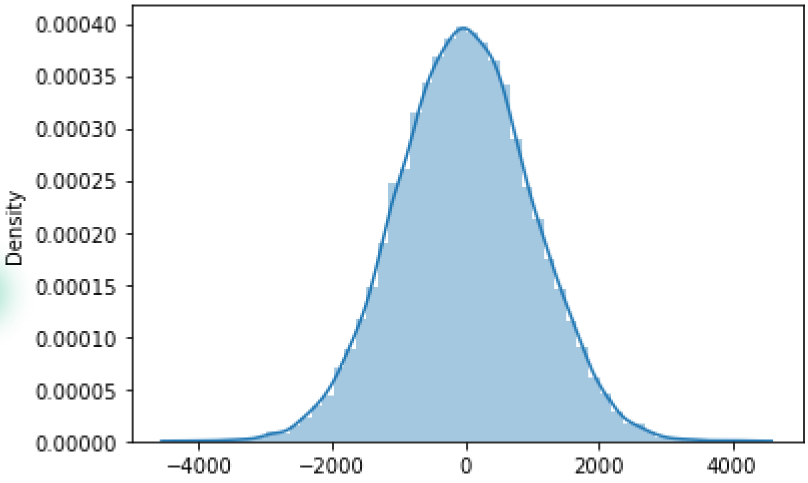
In [21]:

```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

sns.distplot(np.random.normal(loc=0,scale=1000,size=20000),kde=True)
```

```
C:\Users\kisha\anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fu
tureWarning: `distplot` is a deprecated function and will be removed in a fu
ture version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

Out[21]:

```
<AxesSubplot:ylabel='Density'>
```



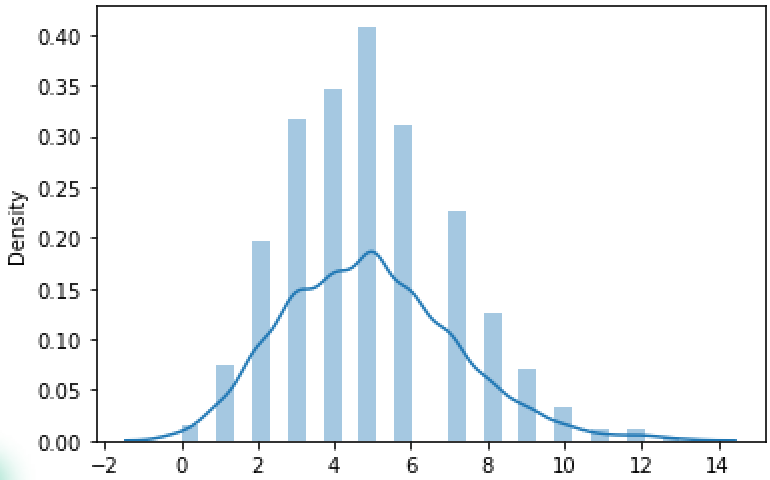
In [22]:

```
sns.distplot(np.random.poisson(lam=5,size=2000),kde=True)
```

```
C:\Users\kisha\anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fu
tureWarning: `distplot` is a deprecated function and will be removed in a fu
ture version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

Out[22]:

```
<AxesSubplot:ylabel='Density'>
```



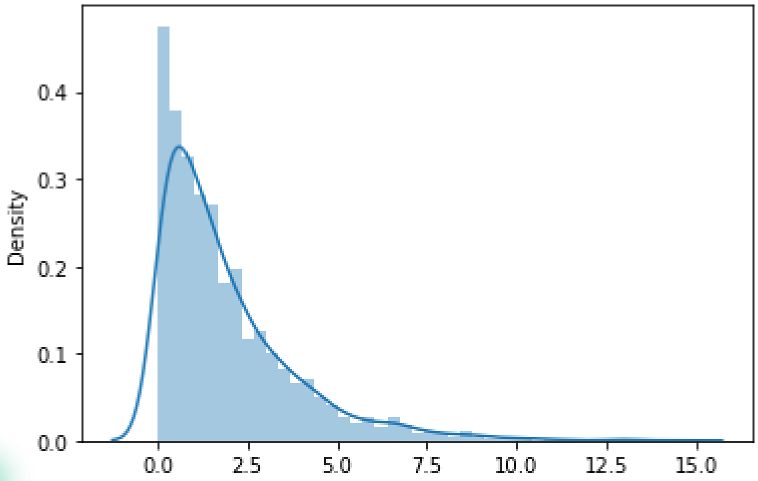
In [23]:

```
sns.distplot(np.random.chisquare(df=2,size=2000),kde=True,hist=True)
```

```
C:\Users\kisha\anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fu
tureWarning: `distplot` is a deprecated function and will be removed in a fu
ture version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

Out[23]:

```
<AxesSubplot:ylabel='Density'>
```



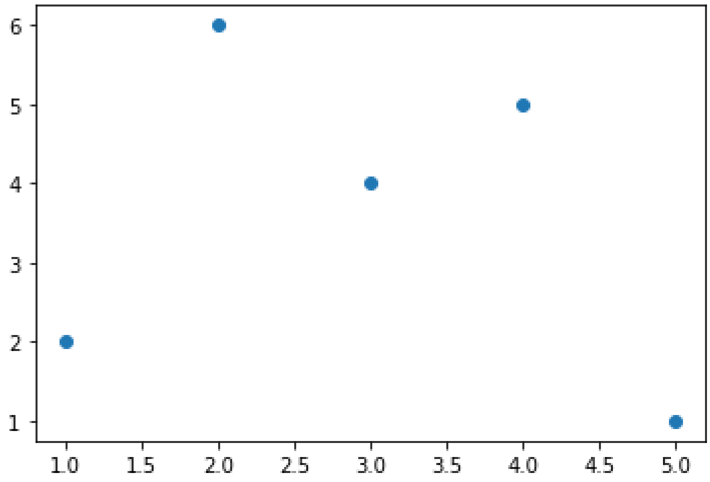
7

In [24]:

```
#scatter
x=[1,3,4,5,2]
y=[2,4,5,1,6]
plt.scatter(x,y)
```

Out[24]:

```
<matplotlib.collections.PathCollection at 0x21b676fa6a0>
```

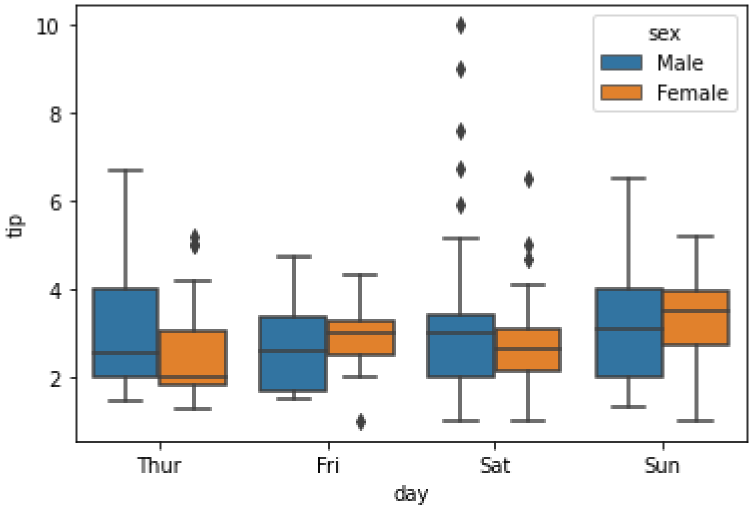


In [25]:

```
#box
dataa=sns.load_dataset('tips')
sns.boxplot(x='day',y='tip',data=dataa,hue='sex')
```

Out[25]:

```
<AxesSubplot:xlabel='day', ylabel='tip'>
```

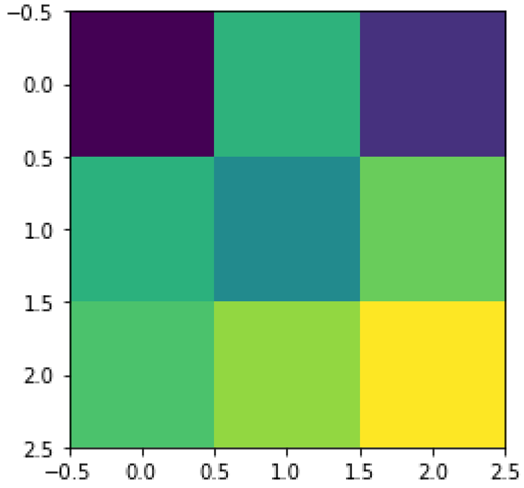


In [26]:

```
j=np.random.rand(3,3)
plt.imshow(j)
```

Out[26]:

```
<matplotlib.image.AxesImage at 0x21b67a6dfa0>
```

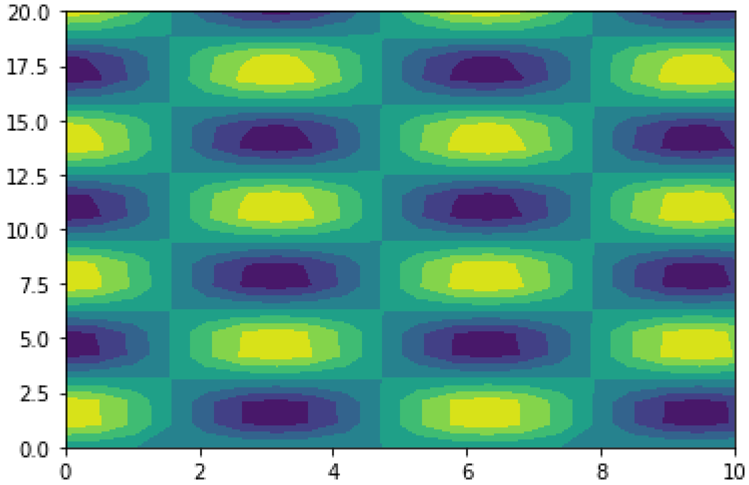


In [27]:

```
f=lambda x,y:np.cos(x)*np.sin(y)
x=np.linspace(0,10,20)
y=np.linspace(0,20,20)
X,Y=np.meshgrid(x,y)
Z=f(X,Y)
plt.contourf(X,Y,Z)
```

Out[27]:

```
<matplotlib.contour.QuadContourSet at 0x21b67ad8a90>
```

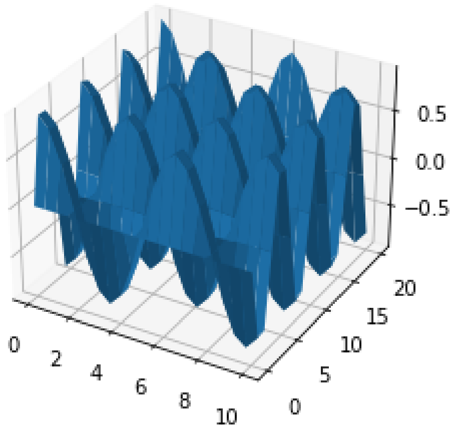


In [28]:

```
import mpl_toolkits.mplot3d
f=lambda x,y:np.cos(x)*np.sin(y)
x=np.linspace(0,10,20)
y=np.linspace(0,20,20)
X,Y=np.meshgrid(x,y)
Z=f(X,Y)
fig=plt.figure()
ax=fig.gca(projection="3d")
ax.plot_surface(X,Y,Z)
```

Out[28]:

```
<mpl_toolkits.mplot3d.art3d.Poly3DCollection at 0x21b67ab31c0>
```



In [29]:

```
import numpy as np

n=np.random.normal(size=1000)
print(np.var(n),
np.std(n),
np.average(n))

n=np.random.chisquare(df=10,size=100)
print(np.var(n),
np.std(n),
np.average(n))

n=np.random.exponential(size=1000)
print(np.var(n),
np.std(n),
np.average(n))

n=np.random.poisson(lam=20,size=10)
print(np.var(n),
np.std(n),
np.average(n))
```

```
1.0370313263599396 1.018347350543978 0.012731873223931704
20.939655746985053 4.57598686044716 9.717569031167173
0.9703376449702846 0.9850571785283759 0.9993109099875217
22.6 4.753945729601885 21.0
```

8

In [30]:

```
#8a
from sklearn.cluster import KMeans

j=sns.load_dataset('iris')
k=j.drop(['petal_length',"petal_width","species"],axis=1)
```

In [31]:

```
km=KMeans(n_clusters=3)
y=km.fit_predict(k)
```

```
C:\Users\kisha\AppData\Roaming\Python\Python38\site-packages\sklearn\cluster
\_kmeans.py:1332: UserWarning: KMeans is known to have a memory leak on Wind
ows with MKL, when there are less chunks than available threads. You can avo
id it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [32]:

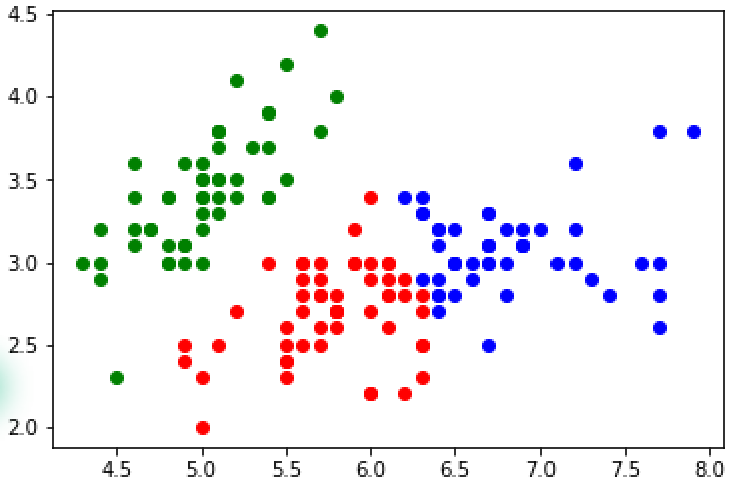
```
k['c']=y
```

In [33]:

```
k1=k[k['c']==0]
k2=k[k['c']==1]
k3=k[k['c']==2]

plt.scatter(k1.sepal_length,k1.sepal_width,color='r')
plt.scatter(k2.sepal_length,k2.sepal_width,color='b')
plt.scatter(k3.sepal_length,k3.sepal_width,color='g')
```

Out[33]:

```
<matplotlib.collections.PathCollection at 0x21b68c6dbe0>
```



In [34]:

```
from sklearn.mixture import GaussianMixture as g
km1=g(n_components=3)
y1=km1.fit_predict(k)
```

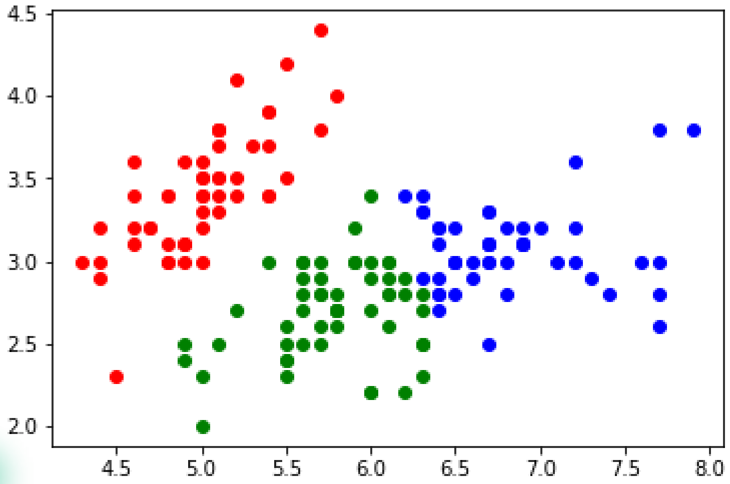
```
C:\Users\kisha\AppData\Roaming\Python\Python38\site-packages\sklearn\cluster
\_kmeans.py:1332: UserWarning: KMeans is known to have a memory leak on Wind
ows with MKL, when there are less chunks than available threads. You can avo
id it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [35]:

```
k['c1']=y1
k1=k[k['c1']==0]
k2=k[k['c1']==1]
k3=k[k['c1']==2]

plt.scatter(k1.sepal_length,k1.sepal_width,color='r')
plt.scatter(k2.sepal_length,k2.sepal_width,color='b')
plt.scatter(k3.sepal_length,k3.sepal_width,color='g')
```

Out[35]:

```
<matplotlib.collections.PathCollection at 0x21b68cef700>
```

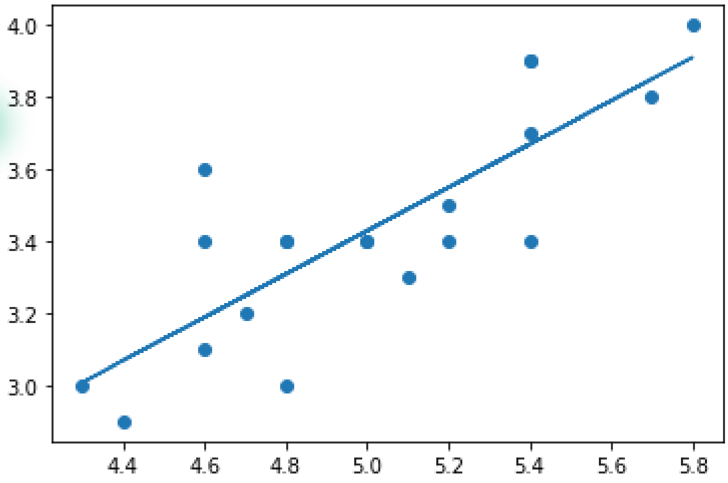


In [36]:

```
from sklearn import linear_model
from sklearn import datasets
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,accuracy_score
k=sns.load_dataset("iris")
x=k.iloc[:30,:1]
y=k.iloc[:30,1:2]

xt,xtr,yt,ytr=train_test_split(x,y,test_size=1/3)


model=linear_model.LinearRegression()
model.fit(xt,yt)
p=model.predict(xt)
plt.scatter(xt,yt)
plt.plot(xt,p)
```

Out[36]:

```
[<matplotlib.lines.Line2D at 0x21b68e37760>]
```



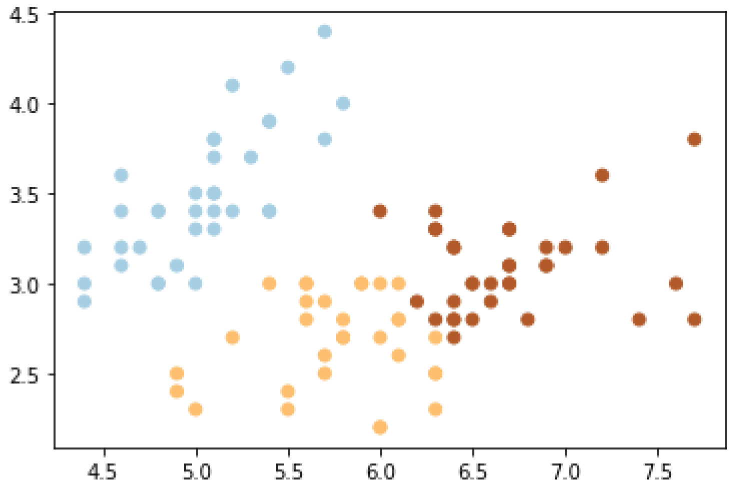
In [37]:

```
from sklearn import linear_model
from sklearn import datasets
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,accuracy_score

j=datasets.load_iris()
x=j.data[:,:2]
y=j.target

xt,xtr,yt,ytr=train_test_split(x,y,test_size=1/3)


model=linear_model.LogisticRegression()
model.fit(xt,yt)
y_pred=model.predict(xt)
print(accuracy_score(yt,y_pred))
print(confusion_matrix(yt,y_pred))

plt.scatter(xt[:,0],xt[:,1],c=y_pred,cmap=plt.cm.Paired)
```

```
0.75
[[35  0  0]
 [ 0 19 13]
 [ 0 12 21]]
```

Out[37]:

```
<matplotlib.collections.PathCollection at 0x21b68ea54c0>
```



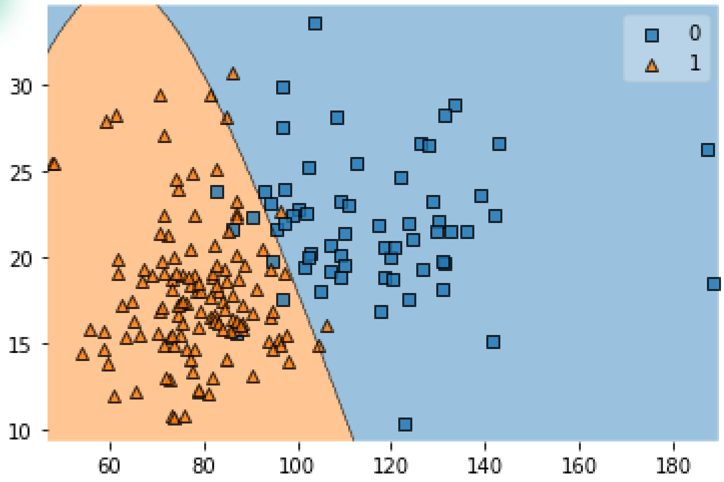
In [40]:

```
dat=datasets.load_breast_cancer()

df=pd.DataFrame(data=dat.data,columns=dat.feature_names)
df['target']=pd.Series(dat.target)

from sklearn.naive_bayes import GaussianNB
features=['mean perimeter','mean texture']

x=df[features]
y=df['target']

xt,xtr,yt,ytr=train_test_split(x,y,test_size=1/3)
mop=GaussianNB()
mop.fit(xt,yt)
prd=mop.predict(xtr)
from mlxtend.plotting import plot_decision_regions
plot_decision_regions(xtr.values,ytr.values,clf=mop)
```

```
C:\Users\kisha\AppData\Roaming\Python\Python38\site-packages\sklearn\base.p
y:450: UserWarning: X does not have valid feature names, but GaussianNB was
fitted with feature names
  warnings.warn(
```

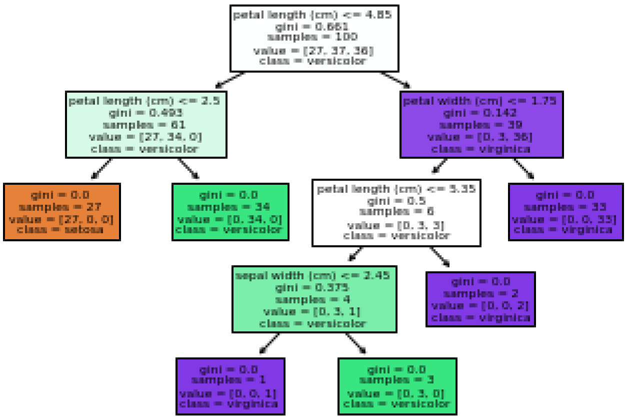
Out[40]:

```
<AxesSubplot:>
```



In [41]:

```
iris=datasets.load_iris()
x=iris.data
y=iris.target
xt,xtr,yt,ytr=train_test_split(x,y,test_size=1/3)

from sklearn.tree import DecisionTreeClassifier as f
from sklearn import tree
mpo=f()
mpo.fit(xt,yt)

_=tree.plot_tree(mpo,feature_names=iris.feature_names,class_names=iris.target_names,filled=
```



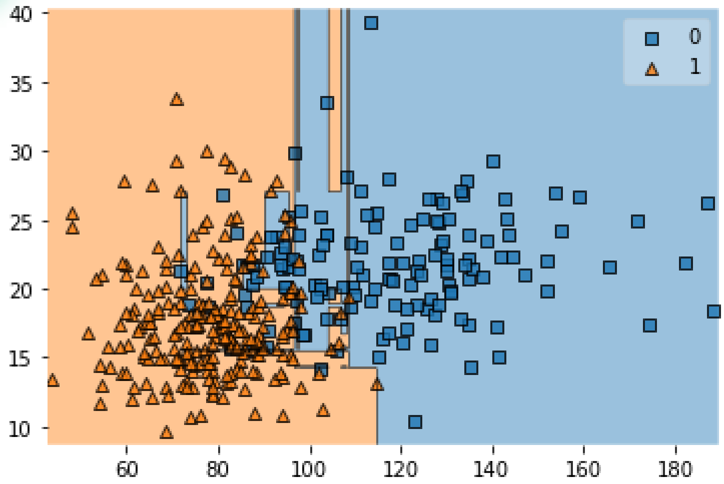
In [42]:

```
from sklearn.ensemble import AdaBoostClassifier as ff
dat=datasets.load_breast_cancer()

df=pd.DataFrame(data=dat.data,columns=dat.feature_names)
df['target']=pd.Series(dat.target)


features=['mean perimeter','mean texture']

x=df[features]
y=df['target']

xt,xtr,yt,ytr=train_test_split(x,y,test_size=1/3)

mpo=ff()
mpo.fit(xt,yt)

plot_decision_regions(xt.values,yt.values,clf=mpo)
```

```
C:\Users\kisha\AppData\Roaming\Python\Python38\site-packages\sklearn\base.p
y:450: UserWarning: X does not have valid feature names, but AdaBoostClassif
ier was fitted with feature names
  warnings.warn(
```

Out[42]:

```
<AxesSubplot:>
```



In [ ]:

```

```